FAULT DIAGNOSTIC ALGORITHM FOR PRECUT FRACTIONATION COLUMN

H. Y. Heng, M. W. Ali*, M. Z. Kamsah

Process Control and Safety Laboratory, Department of Chemical Engineering,
Faculty of Chemical and Natural Resources Engineering, Universiti Teknologi Malaysia,
81310 UTM Skudai, Johor, Malaysia.
*Corresponding author. Phone: +607-5535602, Fax: +607-5581463
Email: m.w.ali@fkkksa.utm.my

ABSTRACT

This paper presents an algorithm which can be used to detect and diagnose unexpected process faults in the operation of fatty acid precut fractionation column. The fault diagnostic algorithm is supported by the process history based method and developed by using Borland C++ Builder 6.0. The fatty acid pre cut fractionation column chosen as a case study is modeled by the commercial simulator, HYSYS.Plant. The discriminator for the detection section is developed by using statistical techniques, where the control limits for each selected monitoring variable were represented in 'High', 'Normal', and 'Low' discrete. Hazard and Operability Study (HAZOP) is used to support the diagnosis task. The algorithm has been successful in detecting the deviations of each variable by testing the data set. The tested data is used to interpret the pattern of the chart, where fault is considered to occur if one variable is out of control limits. The system promptly diagnoses the deviations and gives useful guidance to the user by displaying the causes and consequences of the faults.

Keywords: Fault Detection and Diagnosis, Qualitative Process History Based, HAZOP Study, Statistical Technique

1 INTRODUCTION

Process control community has been successful in removing regulatory control from the hands of human operators to computer automation especially in a complicated plant operation. This has led to great progress in the quest for higher productivity, process safety, process efficiency and profitability. Despite the progress in the distributed and model predictive control systems, managing process plants during the abnormal events and emergencies still remains a manual activity performed by human operators.

The purpose of this research is to develop a detection and diagnosis algorithm supported by knowledge base expert system which is one type of an artificial intelligence tools. One approach of the diagnostic algorithm is to use process history based (Venkatasubramanian *et al.*, 2003). The function of this algorithm is to detect process deviation by using control chart methodology and then provide the information to plant operators. Statistical Process Control (SPC) and HAZOP study are used as the knowledge base and then are constructed into the computer program by using production rules. In this study, a fatty acid fractionation precut column has been chosen as a case study.

2 THEORY

In general, fault can be defined as defect or imperfection of character, structure, or appearance. For the plant or instrumentation, faults are deviations from intended operation. Iserman and Balle (1997) defined fault as an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable, usual and standard condition. Meanwhile, Himmelblau (1978) defined fault as a departure from an acceptable range of an observed variable or a calculated parameter associated with a process.

A diagnostic classifier is generally able to trace any abnormality occurs in a process. A diagnostic system may have them explicitly, or it may be inferred from some source of domain knowledge. The priori domain knowledge may be developed from a fundamental understanding of the process using first-principles knowledge. Such knowledge is referred to as deep, causal or model-based knowledge. On the other hand, the knowledge from past experience with the process is referred to as shallow, compiled, evidential or process history-based knowledge (Venkatasubramanian *et al.*, 2003).

In manufacturing, variations occur in the parameter process. The variations will not only effect the product specification but also will lead to damage and disaster. Principles of statistics are basically considered as technique to detect the variation of parameter. SPC has been established as an important part of quality control in monitoring the values of all process variables and parameters of a product that have an effect on quality and provide the way to monitor chemical and other processes. Process control engineers use SPC to monitor a process's stability, consistency and overall performance.

Lees (1996) has classified hazard analysis methodologies according to the starting point of analysis, the direction of inference and the scope of analysis (qualitative or quantitative). Hazard means inherent potential of a material or activity to harm people, property, or the environment. It does not have a probability component. The specific tool, Hazard and Operability Study (HAZOP), commonly uses a multidisciplinary team to identify, analyze, and control hazards systematically. The main output of this fault detection and diagnostic algorithm concentrate on the location, time, causes, and consequences of process fault.

3 METHODOLOGY

The model of precut fractionation process is developed by using HYSYS.Plant simulator as shown in Figure 1. The precut fractionation column is used for the separation of palm kernel oil. Distillate products consist of C8 and C10 and the net bottom product is pumped to the next columns for further separation. The process involves two types of operation: reflux and pump around. Two separation columns with mixture and accumulator are required to perform the pump around process. In this study, the HAZOP analysis is carried out based on a typical fractionation column as shown in Figure 2.

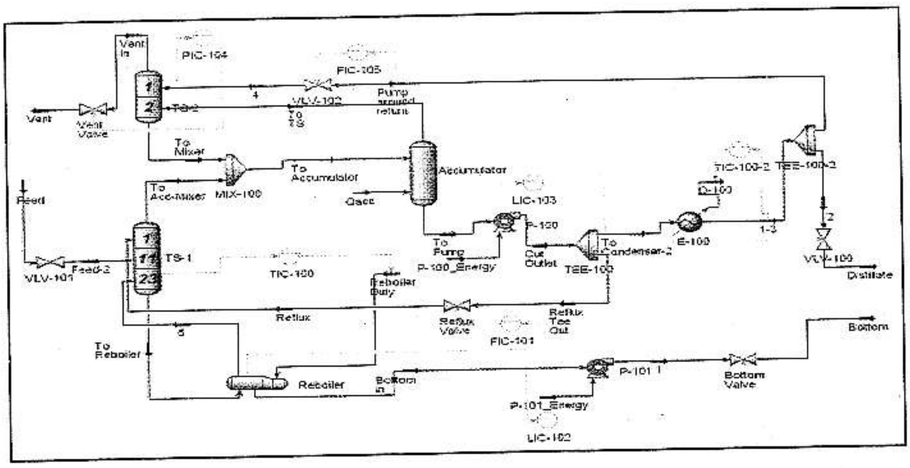

FIGURE 1. Plant model for precut fractionation process

In building the algorithm there are four phases involved as shown in Figure 3. Existing indicator in the fatty acid precut fractionation column are chosen as monitoring variables. Study nodes are defined based on a specific stream or equipment being monitored. HAZOP study is carried out based on these nodes. The definition of nodes is shown in Table 1. The main output of this system includes the location, time, causes, and consequences of process deviation.

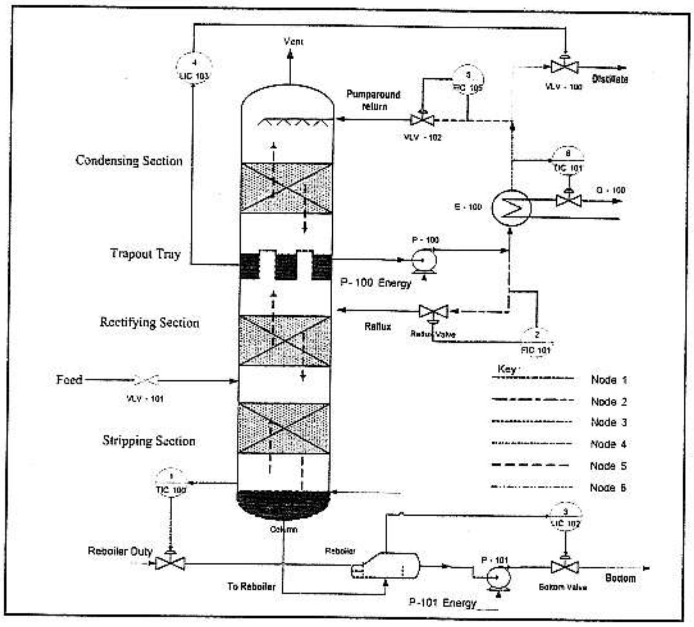

FIGURE 2. Precut fractionation column with study nodes

The diagnostic algorithm is developed by using Borland C++ Builder (BCB) 6.0 programming language. Real plant data, represented by simulated data from plant model developed by using HYSYS.Plant simulator is used to compute control limits. Monitoring variables of the controllers from the plant model such as temperature, and flow rate are chosen as base case to estimate the acceptable range of operation parameter, control limits (X-bar chart, 3-sigma). Analyses such as Autocorrelation, Skewness, Kurtosis, and Boxplot were performed to show that data set was random with normal distribution. Test 1 was chosen to interpret control charts in this case study. In cases where one point goes beyond the 3-sigma limits, fault is considered. Test 1 gives a signal when a signal shifts in the position of mean or an increase in the standard deviation of the process (Nelson, 1985).

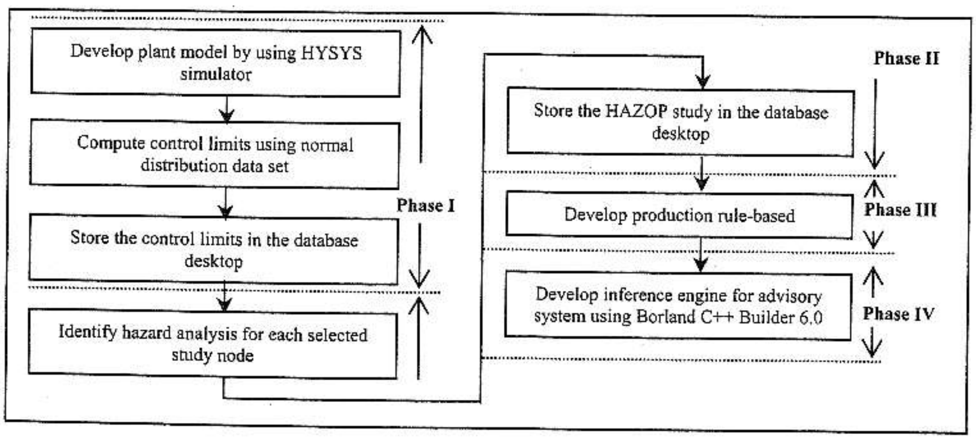

FIGURE 3. Fault Diagnostic System development's flowchart

TABLE 1. Study nodes

Study Nodes	Description
Node 1	Bottom of precut column
Node 2	Stream where Indicator FI 100 is located
Node 3	Level in Reboiler
Node 4	Level at trapout tray
Node 5	Stream where Indicator FI 105 is located
Node 6	Stream where Indicator TI 101 is located

Two types of optimization study are carried out to design the fault diagnosis algorithm. These include the examination of process variables and the sensitivity analysis. The optimization studies are used to determine the exact causes and consequences of the fault that might occur in the plant process. Sensitivity analysis is carried out by using the range that obtained from the analysis for each controller. It was used in HAZOP study to specify the possible causes and consequences of a deviating process. HAZOP study for this research encompasses four lines of stream – study nodes as stated in Table 1. The HAZOP study is also carried out based on the result from sensitivity analysis.

The computed control limits and result of HAZOP study is used in developing two type of rule: Rule I and Rule II. The relationship of Rule I is - *If* 'Variable' and *If* 'Limits', *Then* "Process deviation of monitoring variable". Meanwhile, Rule II is used to reach the end result of fault diagnostic task.

Rule I: *If* TIC 100 and *if* < 236.7523, *Then* 'Low Temperature'.
Then 'Node 1 is Low Temperature & High Flow'.

Rule II: *If* 'Node 1 is Low Temperature & High Flow',
Then 'Node1 Low Temperature & High Flow'*s* Causes, and Consequences'

4 RESULTS AND DISCUSSION

Results for control limits and a sample of HAZOP study are shown in Table 2 and 3 respectively. These knowledge bases are used to develop fault diagnostic algorithm as shown in Figure 4. This system consists of user interface, knowledge base and inference engine. Forward chaining strategy is use to search the knowledge base's examining existing facts and rules and comparing these facts to the information furnished from the process data. For example, a fault is detected based on information by comparing the data process variables with the control limits data. Then, the cause and location of the fault and a suitable countermeasure are then extracted from the knowledge base. Figure 5 shows the prototype that presented the developed algorithm.

TABLE 2. Upper and lower control limits

Sensor variables	Upper Limits (+3σ)	Lower Limits (-3σ)
TIC 100 (° C)	238.3	236.8
FIC 101 (kg/h)	3162	3066
LIC 102 (%)	50.84	49.12
LIC 103 (%)	50.56	49.42
FIC 105 (kg/h)	9001	8197
TIC 101 (°C)	78.8	77.8

TABLE 3. Example of HAZOP study for Node 1

Guide words	Causes	Consequences
High Temperature	Column packing choked and dirty, or collapsed	Precut column overheated
	Reboiler failure	Distillate out of specification
Less Temperature	Stream to reboiler blocked	Low evaporation
	Reboiler failure	Low composition of C8 & C10

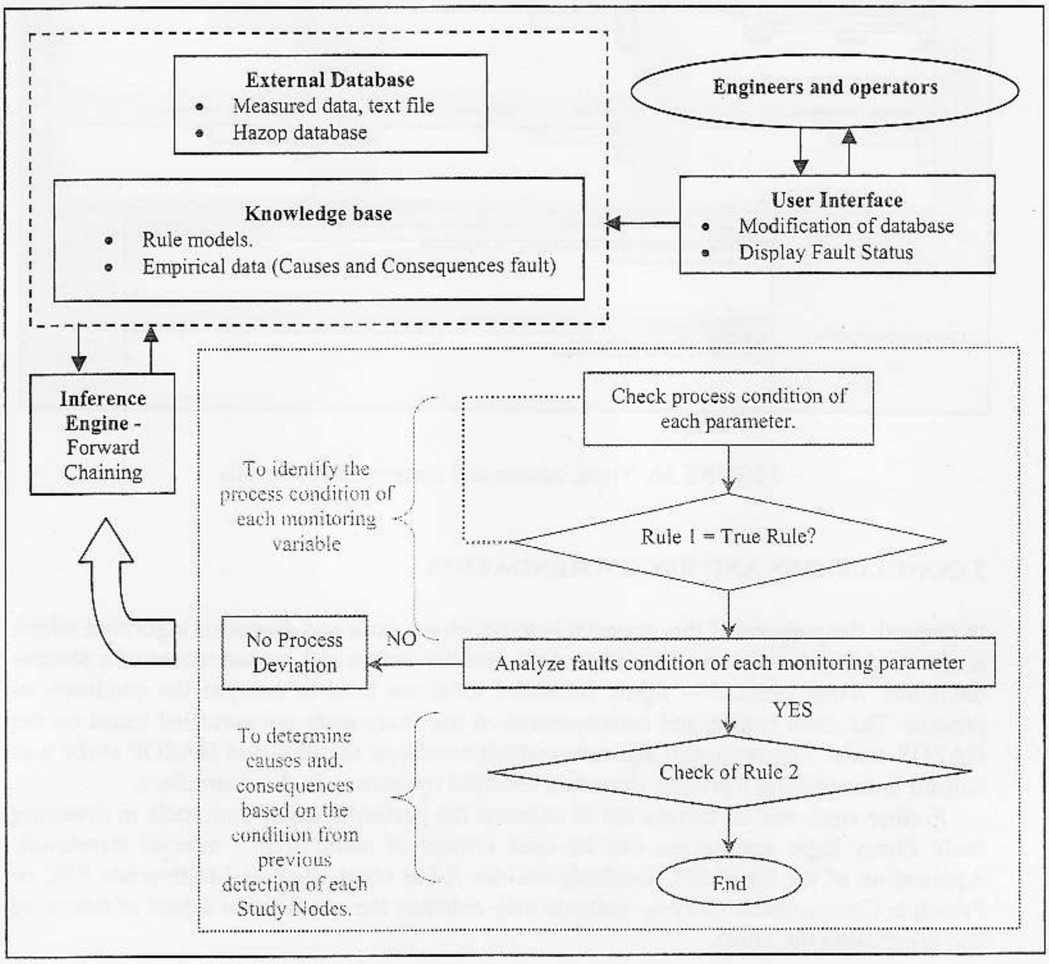

FIGURE 4. Architecture and flow of develop algorithm

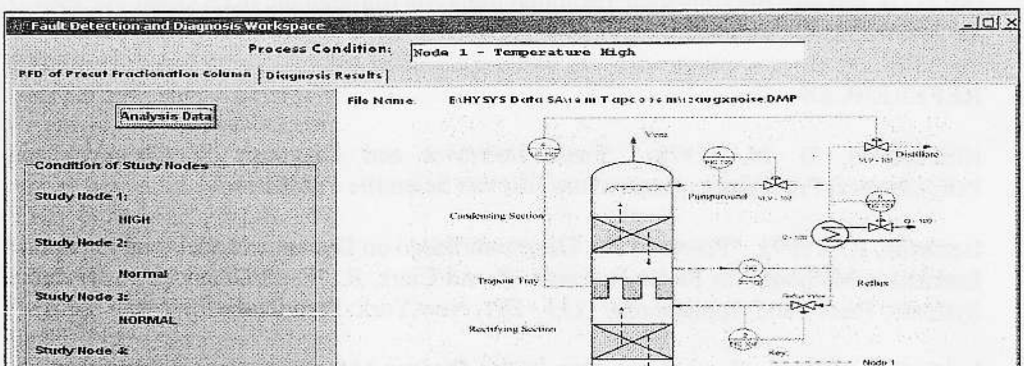

FIGURE 5a. End results of fault diagnostic algorithm

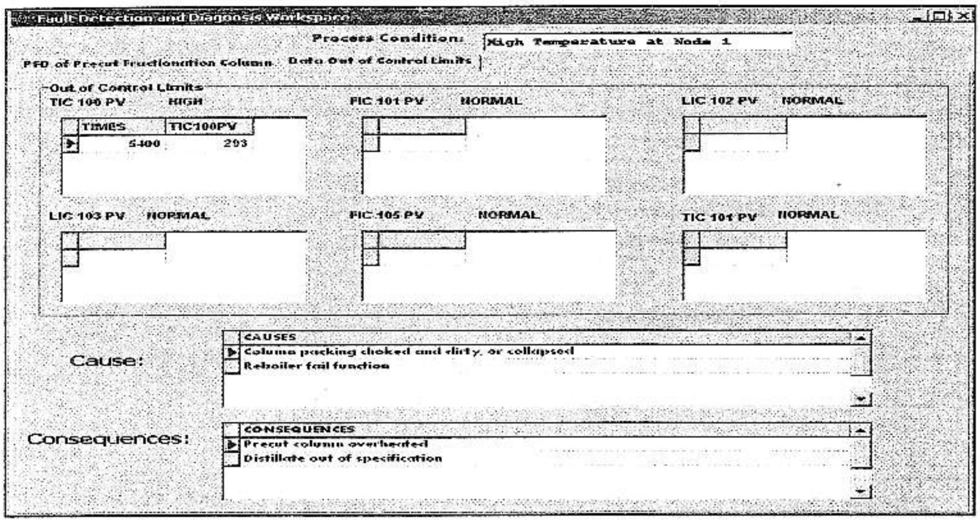

FIGURE 5b. Time, causes and consequences results

5 CONCLUSIONS AND RECOMMENDATION

In general, the purpose of this research is to develop a fault and diagnosis algorithm which is able to determine the exact location, time and the causes and consequences of a process deviation. X-bar chart, 3 – sigma statistical tools are used to analyze the condition of process. The main causes and consequences of the study node are specified based on the HAZOP study. The proposed algorithm which combines the SPC and HAZOP study was helpful in diagnosing a process deviation detected by sensors in the controllers.

Further work can be carried out to enhance the performance of both tools in detecting fault. Fuzzy logic approaches can be used instead of using crisp - interval thresholds. Application of the latest SPC methods besides X-bar chart, such as Multivariate SPC or Principle Components Analysis methods may enhance the quantitative aspect of detecting and diagnosing the faults.

ACKNOWLEDGEMENTS

The authors would like to thank the Ministry of Science, Technology and Innovation (MOSTI), and also the Universiti Teknologi Malaysia (through the IRPA Grant Vot 74015) for sponsoring this research.

REFERENCES

Himmelblau, D. M. (1978). "Fault Detection and Diagnosis in Chemical and Petrochemical Processes". Amsterdam: Elsevier Scientific Publisher.

Isermann, R. (1989). "Process Fault Diagnosis Based on Dynamic Models and Parameter Estimation Methods". In Patton,R. Frank, P. and Clark, R. "Fault Diagnosis In Dynamic Systems. Theory and Applications." 253 - 291. New York: Prentice-Hall.

Lees, F. P. (1996). "Loss Prevention in the Process Industries: Hazard Identification, Assessment and control." Oxford: Butterworth Heinemann.

Nelson, L. S. (1985). "Interpreting Shewhart $\overline{X}$ Control Charts.Technical Aids." Journal of Quality Technology. 17(2): 114:116.

Venkatasubramanian, V., Rengaswamy, R., Yin, K. and Kavuri, S.N., (2003). "A review Of process fault detection and diagnosis Part III: Process history based methods." Computer & Chemical Engineering, 27: 327-346.